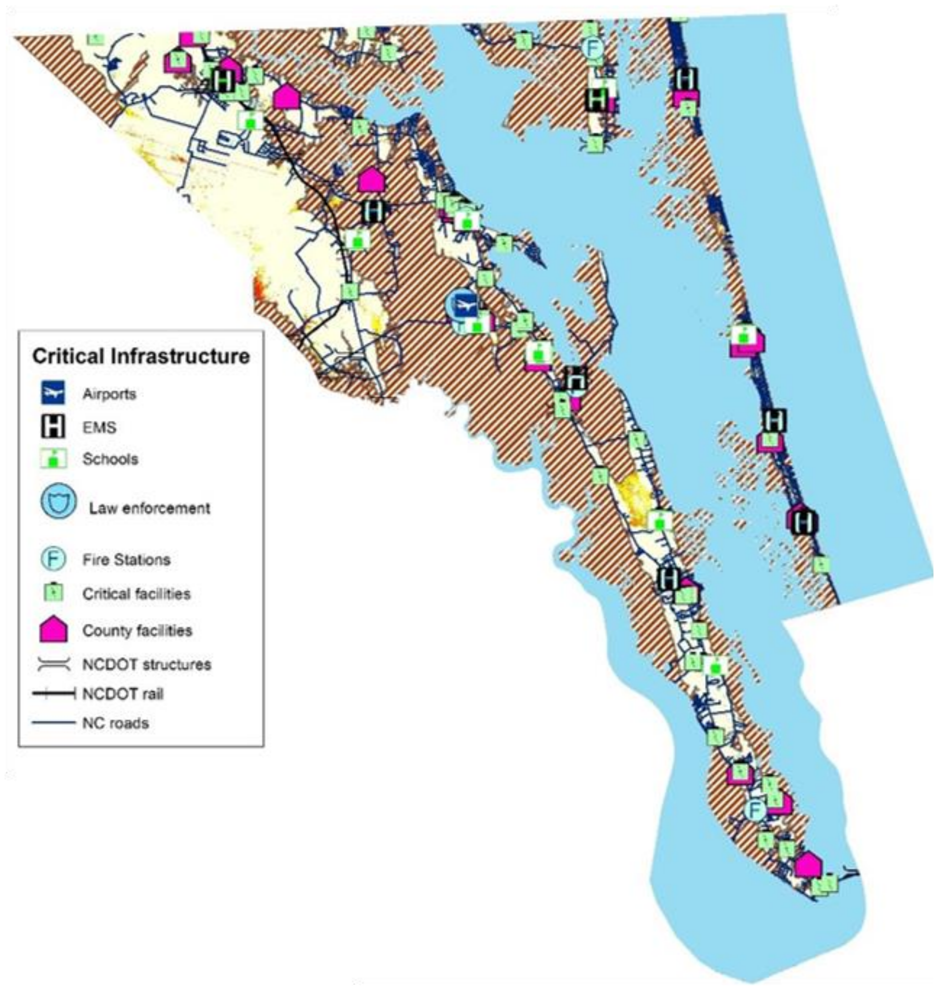


# Currituck County – Coastal Resilience Rainfall Flood Study

Currituck County, North Carolina

Contract #7284

Final Report

Date: August 14, 2018

# CONTRIBUTORS


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## REVISION HISTORY

April 23, 2018 – Draft Report

June 18, 2018 – Final Draft Report

June 29, 2018 – Final Draft Report, with copy edit

August 14, 2018 – Final Report (incorporating NDCEQ comments)

# EXECUTIVE SUMMARY

This study was performed as part of the requirements of Contract No. 7284 between Currituck County and the North Carolina Department of Environmental Quality (NCDEQ). A flood is one of the most severe and potentially devastating natural disasters. Floods come in many forms, such as river, coastal, and flash flooding. Whenever these types of floods occur, long-term planning and adaptation, preparedness and response time are all critical factors in reducing the overall impacts. Awareness of areas that are currently prone and will become more prone to flooding in the future is essential to consider in short-term, as well as long-term planning. A majority of planning activity related to resilience and climate adaptation, both in the region and the State, has focused on coastal flooding and sea level rise. This study focuses on inland flooding, which was identified as an area of limited research, and concerns all communities. The study will also provide an example of work in which other communities can engage. Such awareness comes from an understanding of a combination of not only regional climatic factors, but also of non-climate factors that relate to natural, physical, and developed characteristics.

The current study estimates flood susceptibility in Currituck County due to non-climatic flood risk factors. Several quantitative and qualitative methods were considered to estimate flood susceptibility. The final selected method involves performing a logistic regression. A logistic regression is a statistical method for analyzing a dataset in which there are one or more independent variables that determine a binary (yes or no) outcome. The method uses several flood risk factors that could potentially affect the region and for which sufficient data were available. Flood risk factors considered include elevation, slope, land curvature (concave, convex, or flat), distance to water body, land cover, tree canopy density, surficial materials, soil drainage class, and percent impervious surface. The objective was to link each of the flood risk factors to the occurrence of flooding for a flood event having a recurrence interval of at least 100 years. This would be especially useful in identifying areas susceptible to flooding during extreme events such as Hurricane Matthew, a hurricane that brought rainfall totals, flooding, and a return period of up to 1 in 500 years to northern portions of the county (NOAA, 2017). Due to recent extreme rainfall events over the region, high-resolution satellite images of spatial flood inundation are not available. Alternatively it was decided to use the 100-year FEMA Special Flood Hazard Area (SFHA) to develop a statistical model of coastal flood susceptibility due to storm surge, which has historically been the leading cause of flooding in Currituck County.

Prior to developing the flood susceptibility map for Currituck County, the entire county was divided into more than 1,722,000 "30m x 30m" cells. Approximately 5 percent of the cells (86,122 cells) covering a total area of near 30 square miles were randomly chosen throughout Currituck County from which to extract data for each flood risk factor (refer to Table A-1 for data source information). An equal number of these points were selected in locations that were within and outside of the SFHA. The data for each flood risk factor were selected from all locations using ArcGIS and associated with a '1' if the location was within the floodplain and a '0' otherwise. The resulting relationships between each factor and flood occurrence were ingested into a logistic regression from which a regression coefficient was obtained for each flood risk factor. The magnitude of the coefficients indicates the relative strength of each flood risk factor's influence on flooding. It was found that 'elevation', 'land slope', and 'soil drainage type' have the most influence on flood susceptibility throughout the county. The final logistic regression equation that was developed was then used to assign probabilities of flooding to all locations to create an overall probability map of Currituck County. Probabilities were classified within one of five classes: 0 – 20% ("very low risk"); 20 – 40% ("low risk"); 40 – 60% ("medium risk"); 60 – 80% ("high risk"); and 80 – 100% ("very high risk"). Several types of critical infrastructure were overlaid on the flood susceptibility map to identify those assets that are most vulnerable to the 100-year flood. It was observed that several areas classified as "very high risk" and "high risk" and that contained several types of critical infrastructure were located in the central portion of the county as well as along the northern Outer Banks. Almost all such high-risk areas in the central region fell within the FEMA SFHA, while several locations exhibiting 'medium' to 'very high' risk along the Outer Banks were located outside the SFHA; infrastructure within these 'sub-region' warrants additional attention regarding potential flood mitigation efforts.

It should be noted that the FEMA 100-year SFHA is limited to the sub-watersheds of greater than one square mile that FEMA chose to study with limited resources. Other limiting factors are the age of the underlying studies illustrated by the FEMA maps (often more than two decades old) and their focus on only areas where development existed or was imminently anticipated. FEMA's flood mapping is developed using physical models to perform hydrologic and hydraulic analysis of a statistical flood event with a one percent chance of being equaled or exceeded in any given year (referred to as the 100-year flood). The susceptibility maps from this study provide a less expensive approach of covering all land area within the region. By using the statistical modeling methodology described in this report it was possible to identify the contribution of flood factors within the physically modeled FEMA SFHA and apply them to the entire study region to identify areas thought to be vulnerable to flooding. One important disclaimer is that the flood susceptibility map was created for present-day conditions and is only to be used for planning purposes; it is not intended to replace the FEMA mapping for regulatory or flood insurance decisions.

# TABLE OF CONTENTS

# 1. INTRODUCTION

This study was performed as part of the requirements of Contract No. 7284 between Currituck County and the North Carolina Department of Environmental Quality (NCDEQ). A flood is one of the most severe and potentially devastating natural disasters. Flooding occurs in many forms, such as river, coastal, and flash flooding. These flood events arise from a variety of processes such as snow melt, severe precipitation events, storm surge, and on a more long-term scale, relative sea-level rise. Whenever any of these types of flooding events occur, long-term planning and adaptation, preparedness and response time are all critical factors in reducing the overall impacts. Up until the year 2013, there had been no significant trend in the severity of flooding in North Carolina (Peterson et al., 2013). However, flooding, according to NOAA, was the second-most common natural hazard in North Carolina during the period 1996 - 2014 (first is thunderstorm & lightning), with a flood occurring an average of once every 7.6 days (USDOE, 2015). During the same period flooding resulted in the third largest annualized property loss due to natural hazards behind hurricanes and tornados. Awareness of areas that are more prone to flooding is essential to consider in long-term planning. It can also inform short term strategies, such as the development of early warning mechanisms. Such awareness comes from an understanding of a combination of not only climatic factors impacting the region, but also of non-climate factors that relate to regional and site characteristics as well.

Various types of hydrological models can be used to model flood susceptibility and can be categorized as conceptual, physically-based, or data-driven models. Conceptual models are typically comprised of partial differential equations of continuity and momentum, which can result in an accurate estimation of the internal mechanisms of the hydrological processes. Conceptual models do require a large amount of calibration data and sophisticated analysis tools, which is not within the scope of the current project. Physical models are based on an understanding of complex physical processes, which can be effectively used for long-term flood forecasting and reducing associated damages in a river basin. Rainfall/runoff models are one of the most common models of this type. The disadvantage is that a large amount of time and resources is often required to understand the complex physical processes that are a part of these models. Physical models also require tremendous amounts of data for calibration and validation along with long computation times.

Data-driven models alternatively use linguistic variables whose values include words or phrases, rather than the conventional numerical variables used in the models described above. Data-driven models extract information from the input/output datasets used to create the model to develop a statistical correspondence between the data. Unlike physical models, they do not require an understanding of the complex physical processes by which the data are related, only an understanding of the hydrological and meteorological variables and regional characteristics that influence flood risk. The assumption that future flooding occurrences will occur under similar conditions as past events with respect to these non-climatic flood risk factors needs to be made in such a model. The objective in most data-driven models is to produce a list of relative weights for whatever flood risk factors have been identified. These weights can then be used to produce a risk map. The method used to derive these weights represents the major difference between the models. Therefore, there are two major decisions that need to be addressed when using a data-driven model. The first decision involves the specific method to be used, while the second decision identifies the flood risk factors that will be addressed and weighted, if required, using the selected method.

## 2. LITERATURE REVIEW

Examples of data-driven models found in the literature include fuzzy logic (FL), artificial neural networks (ANN), adaptive neuro-fuzzy interface system (ANFIS), and analytical hierarchy process (AHP). The first of these models is Fuzzy Logic, which is set up using flood risk factor membership functions and rules. The membership function for each factor incorporates various classifications (e.g. high, medium, and low) of that factor. After the variables are partitioned into their different “fuzzy” classes, an IF…THEN type of rule is set up to establish the response of any combination of these “fuzzy” classes. For example, Gogoi and Chetopa (2011) used a fuzzy rule-based model to forecast runoff in the Jiadhal Basin in Northeast India. The authors used three flood risk factors (total monthly rainfall, mean monthly temperature, previous month’s discharge) and three categories (e.g. high, medium, and low) to describe projected runoff, resulting in a total number of 33 = 27 rules. Sets of values for each variable were then tested against these rules to identify rules that are fulfilled to a point that exceeds a certain threshold value. This final set of rules was then used to project runoff based on values of the identified flood risk factors.

The second type of data-driven model is the Artificial Neural Network (ANN). ANNs consist of layers of nodes or neurons, which include an input layer (number of neurons equals the number of flood causative factors), an output layer (number of neurons equals the number of types of desired outputs), and one or more hidden layers where algorithms are used to model the complex relationships that exist between each flood causative factor and the influence that they have on the output, which in the context of flooding would be water levels and/or flow. Kia et al. (2012) used ANN to predict water levels and flood inundation using seven potential flood causative factors: rainfall, slope, elevation, flow accumulation, soil, land use/cover, and geology. Alternatively, the third model type is the Adaptive Neuro-Fuzzy Inference System (ANFIS), which uses a combination of the numeric power of neural networks and the verbal power of fuzzy logic. Such a model contains features of both types of models such as learning and optimization abilities and "if-then" rule thinking to map an input space to an output space. An example of this method was developed for the Barak River basin in Northeast India by Ullah and Choudhury (2013). Issues with using an ANN, ANFIS, or any method that incorporates neural networks, relates to their complexity and the high computing power that is required to run the algorithms. Also, the quality of the resulting predictions in many cases have been found to be inferior to other model types (Shortridge et al., 2016), especially when the data used to validate the model contains values outside the range of data used to train the model.

An alternative to the data-driven methods above is the Analytic Hierarchy Process (AHP). AHP identifies potential flood risk factors and their associated weights using expert opinions combined with geographical, statistical, and historical data. For example, Matori et al. (2014) and Siddayao et al. (2014) used AHP in performing spatial assessments of floodplain risk in northern Malaysia and the northern Philippines, respectively. Flood risk factors included rainfall, geology, soil type, land use, population density, distance from riverbank and site elevation and slope. The authors in both studies surveyed experts in the region and used the survey results to develop weights for each factor. They combined the resulting weights with a Geographical Information System (GIS) to produce a color-coded map representing various levels of risk for each respective study region. The advantage of this method is that the final product is a flood susceptibility map based on the combined experience of several years of flooding events from various type of experts who are familiar with the region. The disadvantage is that the results can be based on subjective and conflicting opinions, especially when there are many flood risk factors being considered. This can be alleviated, however, when using the overall factor weighting mechanisms that are typically used in AHP.

Other quantitative types of data-driven models include multivariate statistical analysis (MSA) and multivariate logistic regression (MLR), or some combination of these. These methods rely on numerical expressions that characterize the relationships between the independent flood risk factors and flood inundation (Lee et al. 2012). The use of MSA typically requires several strict assumptions to be made prior to the analysis and requires the relationship between flooding and each flood risk factor to be considered independently from any potential relationships between factors to develop weights for each factor. MLR can be used to solve this issue by examining the relations between a dependent variable (e.g., whether a location is flooded or not flooded) and any number of independent variables (e.g. flood risk factors; Pradhan 2010). An advantage of MLR is that a separate analysis is not required to estimate the weight of each flood risk factor as this functionality is already built into such coding environments as R. Another advantage of MLR is that the variables can be continuous and/or categorical and is straightforward to implement.

After considering the advantages and disadvantages of each modeling approach described above and the project scope, MLR was selected for the current study.

# 3. DATA AND METHOD

The current work was conducted in Currituck County, NC, (location shown in Fig. 2-1), the most northeastern county in North Carolina. Currituck County includes the northern communities of North Carolina's Outer Banks, which are separated from the mainland by Currituck Sound. Currituck County is known for its pristine beaches, rich farmland, numerous wildlife refuges, and the Corolla wild horses. In order to preserve these resources, which help to maintain the county's tourism industry, awareness of flooding susceptibility, particularly due to storm surge and heavy precipitation as a result of hurricanes and other coastal storm events and riverine flooding, is very important in this region. The potential impacts on tourism can be economically devastating. Spatially, Currituck County consists of half-open water and half land area. Therefore, the county takes its identity from its coastline, making it imperative to plan properly to preserve and live in harmony with these resources.

## 3.1. Flood Risk Factors

There are several types of data that are required as independent variables when performing any type of flood susceptibility study. These independent types of data represent parameters that may contribute to flooding in a region, and are referred to as flood risk factors. Flood risk factors utilized for flood susceptibility mapping should be measurable and collected throughout the entire "Area of Influence" (AOI). However, they should not represent information that is spatially uniform. Although there is no agreement on which risk factors are the standard for any flood susceptibility analysis, there are factors that are more prominently used than others. Some of the most common factors are listed in Table 2-1 along with the citations for a few of the studies in which they were identified as influential.

A subset of the flood risk factors listed in Table 2-1 was chosen for the present study after considering the availability, period of record, and completeness of each dataset as applied to Currituck County. This subset includes the following factors: elevation, slope, land curvature, land cover, distance to water body, tree canopy density, percent impervious surface, soil drainage class, and geology. Abbreviations, sources, and the resolution/scale of each dataset are given in Table A-1 in Appendix A. These flood risk factors were collected over the present study's AOI, which is defined as a polygon having boundaries that extend slightly outside of the boundaries of Currituck County (refer to Fig. 2-1) and compiled into spatial databases using the ArcGIS 10.2 software. All datasets were resized using linear interpolation to a 30 m x 30 m grid comprised of a total of more than 1,722,000 cells.

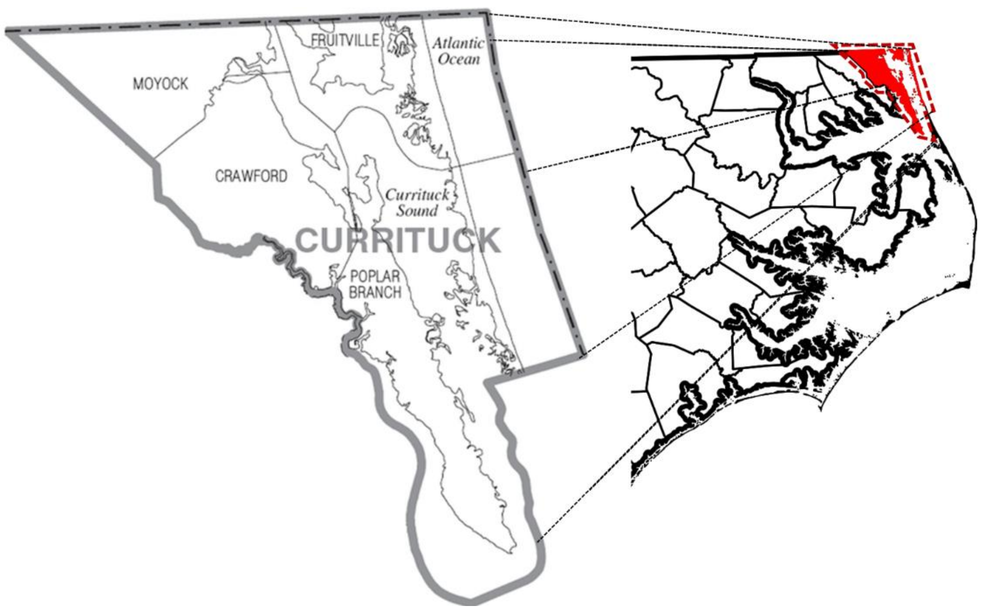



Figure 2-1: Map showing the location of Currituck County (shaded red) and the "Area of Influence" (red dashed line) within the northeast corner of the State of North Carolina.

Table 2-1: Flood risk factors and examples of studies where they have been considered.

| Flood Risk Factors | Literature |
|---|---|
| **Temperature** | Gogoi & Chetia (2011) |
| **Previous month's discharge** | Gogoi & Chetia (2011) |
| **Population Density** | Siddayao et al. (2014); Sinha et al. (2008); Zhang et al. (2005) |
| **Distance from Riverbank** | Siddayao et al. (2014) |
| **Landform: slope/elevation/curvature** | Matori et al. (2014); Siddayao et al. (2014); Tehrany et al. (2014); Lawal et al. (2012); Saini & Kaushik (2012); Sinha et al. (2008); Zhang et al. (2005) |
| **Distance from access road** | Harrison & Qureshi (2003) |
| **Land-use zoning** | Lawal et al. (2012); Harrison & Qureshi (2003) |
| **Drainage density** | Lawal et al. (2012); Saini & Kaushik (2012) |
| **Proximity to drainage** | Sinha et al. (2008) |
| **Soil type/drainage** | Matori et al. (2014); Tehrany et al. (2014); Lawal et al. (2012); Saini & Kaushik (2012); Yahaya (2008) |
| **Distance from urban areas** | Harrison & Qureshi (2003) |
| **Precipitation/rainfall** | Matori et al. (2014); Tehrany et al. (2014); Lawal et al. (2012); Gogoi & Chetia (2011); Yahaya (2008); Zhang et al. (2005); Harrison & Qureshi (2003) |
| **Land cover/use & Vegetation** | Matori et al. (2014); Tehrany et al. (2014); Saini & Kaushik (2012); Yahaya (2008) |
| **Geology** | Matori et al. (2014); Tehrany et al. (2014) |
| **Timber type/size/density** | Tehrany et al. (2014) |

Prior to using each data set in the flood susceptibility analysis, each flood risk factor was divided into classes. This is accomplished using the quantile method (Tehrany et al., 2014; Umar et al., 2014; Papadopoulou-Vrynioti et al., 2013), which partitions each numerical data set (e.g. elevation (0.0 – 59.8 m), land slope (0.0 – 13.5°), land curvature (-0.67 - 1.66), which represents the shape of the land and identifies local low points (concave) and high points (convex), tree canopy density (0.0 – 100.0%), distance to water body (0 – 25,000 m), and percent impervious service (0.0 – 100.0%)) into classes containing the same number of features or pixels. Partitioning the data in this manner ensures that data is included and that a coefficient can later be determined for each flood risk factor class. For the purposes of this study, each of these datasets was divided into 10 categories, excluding impervious surface, which was divided into 6 classes, using the classifications given in Table 2-2; refer to Figs. 2-2 – 2-7, respectively, to view the spatial distributions of each class. Regarding the other datasets, land cover was divided into 11 classes (Fig. 2-6); soil drainage class was divided into 8 classes (Fig. 2-8); and surface geology was divided into 3 classes (Fig. 2-10).

Table 2-2: Regression coefficients for each class of each flood risk factor.

| Factor | Class | Logistic Coefficient | Factor | Class | Logistic Coefficient |
|---|---|---|---|---|---|
| **$a_0$** | -- | 12.6325 | DIST(m) | 0.00 – 0.00 | 0.0000 |
| **ELEV(m)** | < 0.94 | 0.0000 | | 0.01 – 196.21 | 0.0000 |
| | 0.94 – 1.41 | 0.6128 | | 196.21 – 490.52 | -0.4004 |
| | 1.41 – 2.11 | -0.3583 | | 490.52 – 784.83 | -0.9168 |
| | 2.11 – 4.22 | -3.0786 | | 784.83 – 1,177.25 | -0.9724 |
| | 4.22 – 6.10 | -6.4254 | | 1,177.25 – 1,667.77 | -1.1524 |
| | 6.10 – 7.51 | -9.3953 | | 1,667.77 – 2,452.61 | -1.4200 |
| | 7.51 – 9.15 | -11.3555 | | 2,452.61 – 3,727.97 | -1.5727 |
| | 9.15 – 11.03 | -12.0374 | | 3,727.97 – 6,867.30 | -1.2850 |
| | 11.03 – 14.08 | -11.1318 | | 6,867.30 – 25,016.61 | 0.5664 |
| | 14.08 – 59.82 | -9.4493 | IMP(%) | 0.00 – 0.00 | 0.0000 |
| **CURV** | < -0.0247 | 0.0000 | | 0.01 – 4.00 | -1.0587 |
| | -0.0247 – -0.0156 | 0.4361 | | 4.01 – 14.00 | -0.7813 |
| | -0.0156 – -0.0064 | 0.7605 | | 14.01 – 47.00 | -0.4579 |
| | -0.0064 – 0.0027 | 0.8901 | | 47.01 – 100.00 | 0.7882 |
| | 0.0027 – 0.0118 | 1.0959 | GEO | Sediments - fine | 0.0000 |
| | 0.0118 – 0.0210 | 1.3195 | | Sediments - medium | -0.2054 |
| | 0.0210 – 0.0301 | 1.4729 | | Organic rich muck/peat | 2.0944 |
| | 0.0301 – 0.0392 | 1.6368 | LAND | developed, open space | 0.0000 |
| | 0.0392 – 0.0667 | 1.7871 | | dev., low intensity | 0.6185 |
| | 0.0667 – 1.656 | 1.8627 | | dev., medium/high intensity | -0.0334 |
| **SLOPE** | 0.0000 – 0.0000 | 0.0000 | | barren land | 1.0416 |
| | 0.0001 – 0.0530 | -2.6134 | | forest (ever./dec./mixed) | -0.6885 |
| | 0.0530 – 0.1060 | -2.7826 | | shrub/scrub | -0.8099 |
| | 0.1060 – 0.1591 | -2.6321 | | herbaceous | -0.5439 |
| | 0.1591 – 0.2121 | -2.6346 | | hay/pasture | -1.0040 |
| | 0.2121– 0.3181 | -2.6122 | | cultivated crops | -1.1890 |
| | 0.3181 – 0.4241 | -2.4032 | | Woody wetlands | -0.0645 |
| | 0.4241 – 0.5832 | -2.4183 | | Emergent herbaceous wetlands | 0.7131 |
| | 0.5832 – 0.9013 | -2.5059 | TREE(%) | 0.00 – 0.00 | 0.0000 |
| | 0.9013 – 13.5197 | -2.3585 | | 0.01 – 39.00 | 0.2313 |
| **SOIL** | unrated | 0.0000 | | 39.01 – 70.00 | 0.2404 |
| | very poorly drained | -2.4643 | | 70.01 – 83.00 | 0.2305 |
| | poorly drained | -1.6092 | | 83.01 – 89.00 | 0.0422 |
| | somewhat poorly | -1.7349 | | 89.01 – 92.00 | 0.0653 |
| | moderately well | -1.6259 | | 92.01 – 96.00 | -0.0565 |
| | well drained | -2.2206 | | 96.01 – 98.00 | -0.0014 |
| | somewhat excessively | 0.0000 | | 98.01 – 99.00 | -0.0862 |
| | excessively drained | -0.6522 | | 99.01 – 100.00 | 0.3439 |

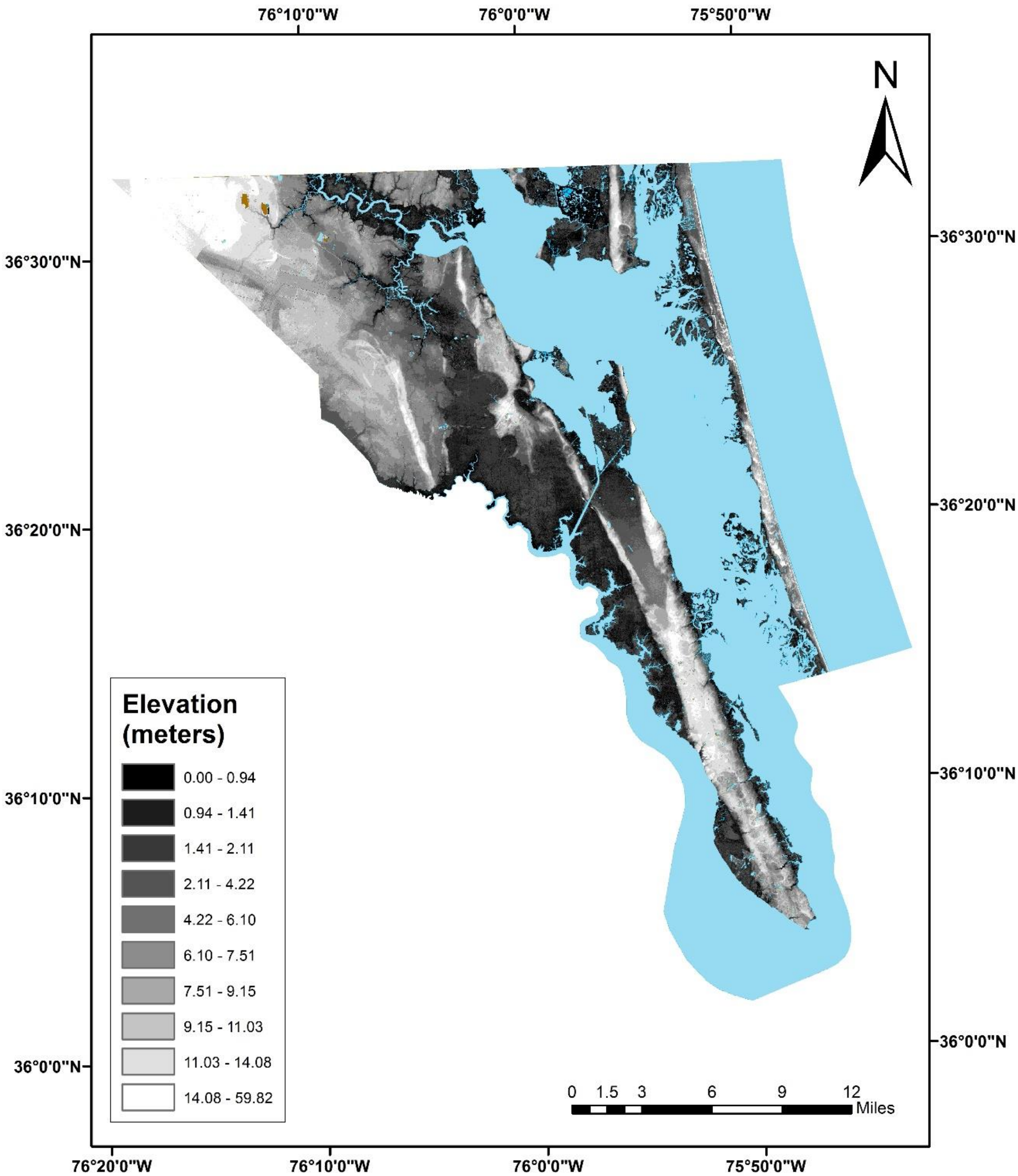



Figure 2-2: Spatial distribution of flood risk factor “elevation”. (Source: https://earthexplorer.usgs.gov)

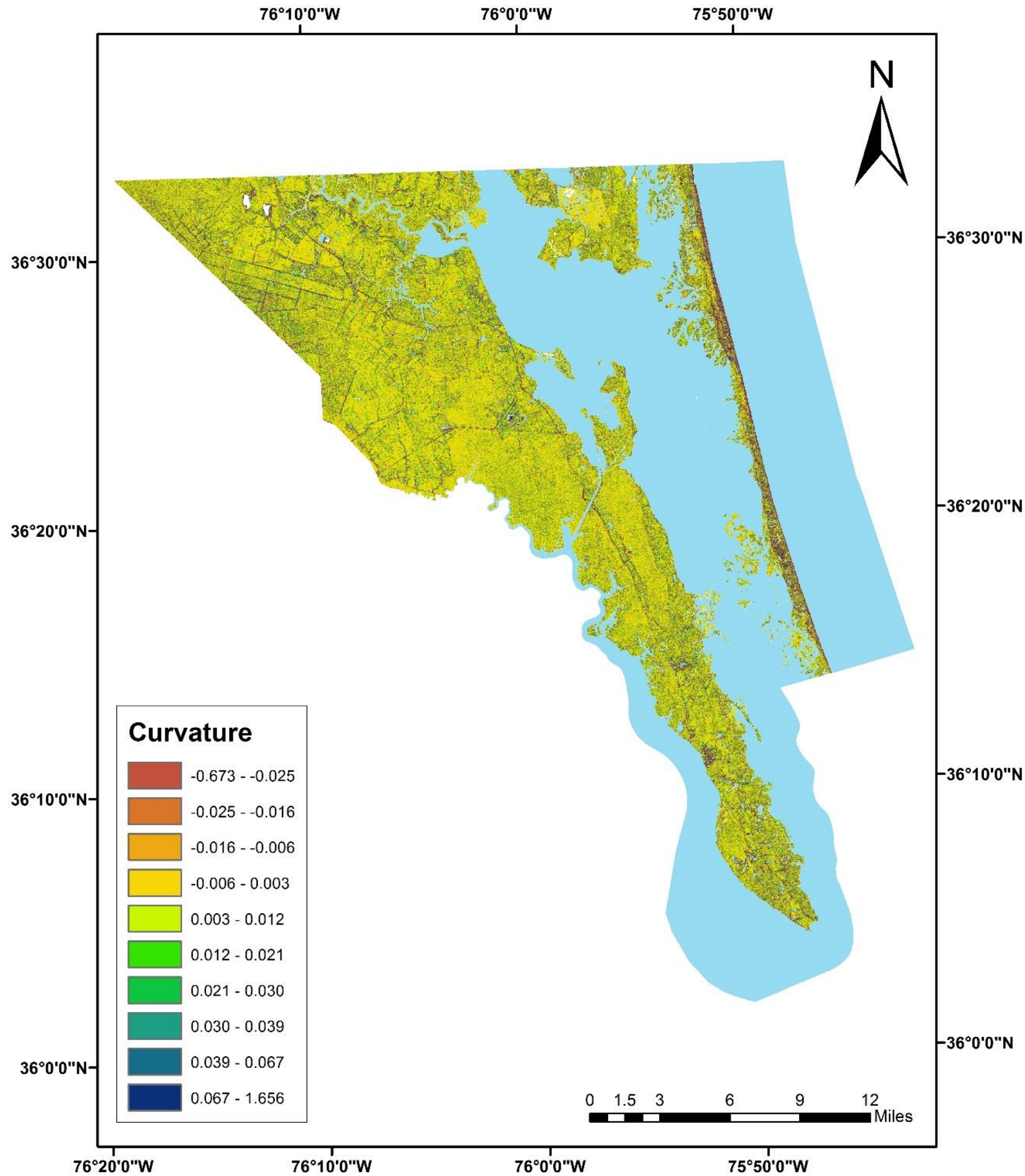



Figure 2-3: Spatial distribution of flood risk factor “curvature”. (Source: https://earthexplorer.usgs.gov)

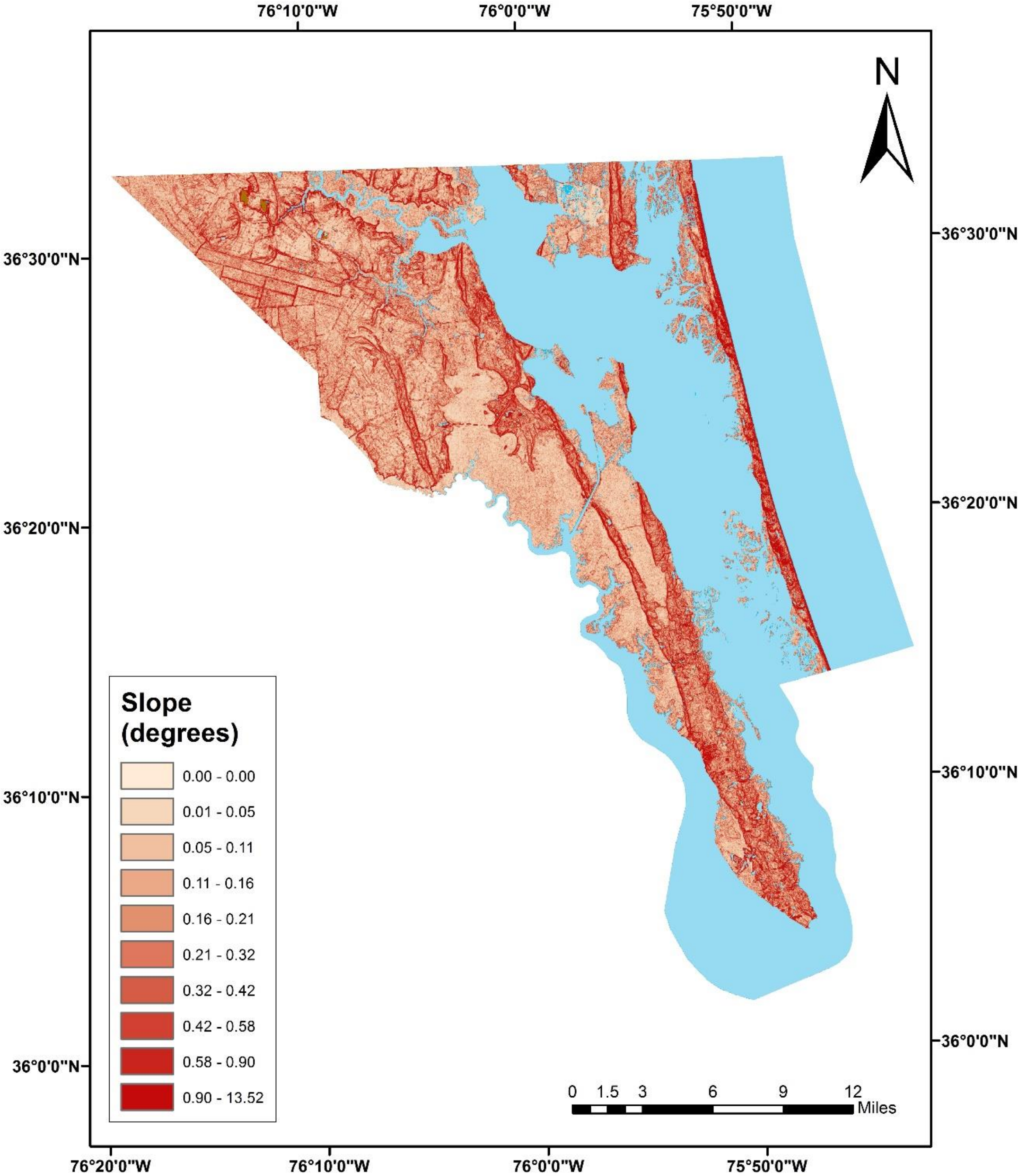



Figure 2-4: Spatial distribution of flood risk factor “slope”. (Source: https://earthexplorer.usgs.gov)

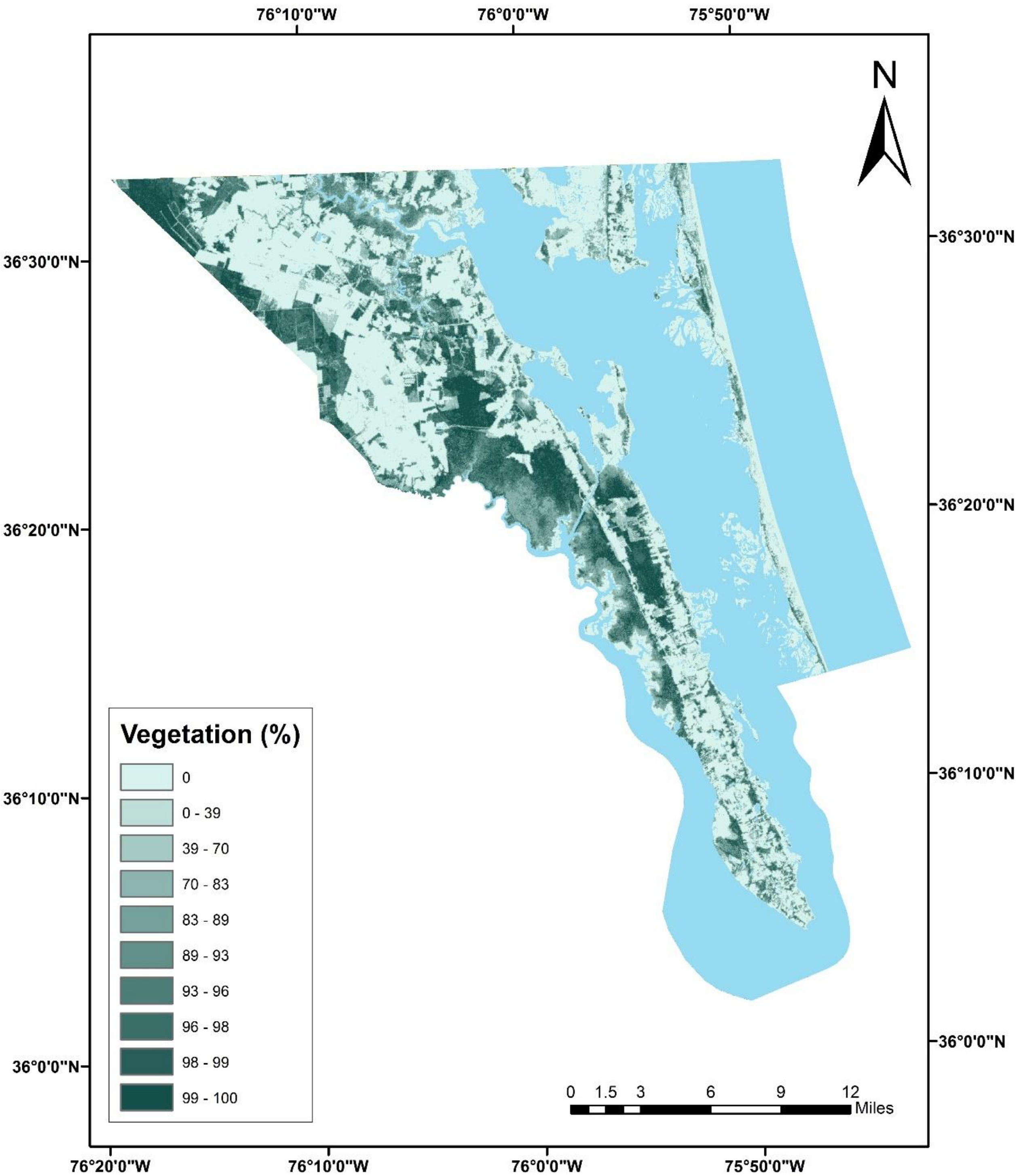



Figure 2-5: Spatial distribution of flood risk factor “tree canopy density”. (Source: https://www.mrlc.gov)

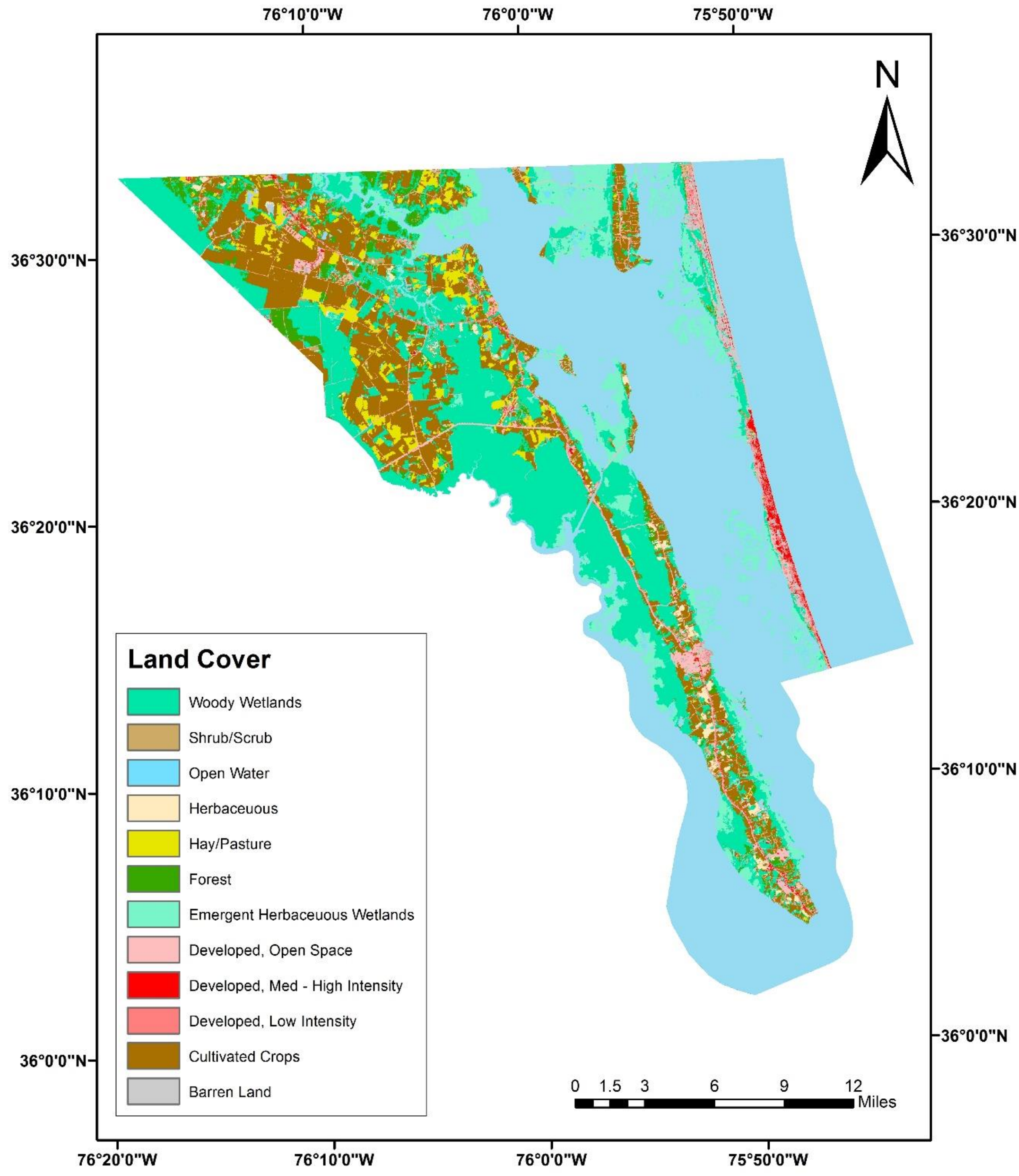



Figure 2-6: Spatial distribution of flood risk factor "land cover". (Source: https://www.mrlc.gov)

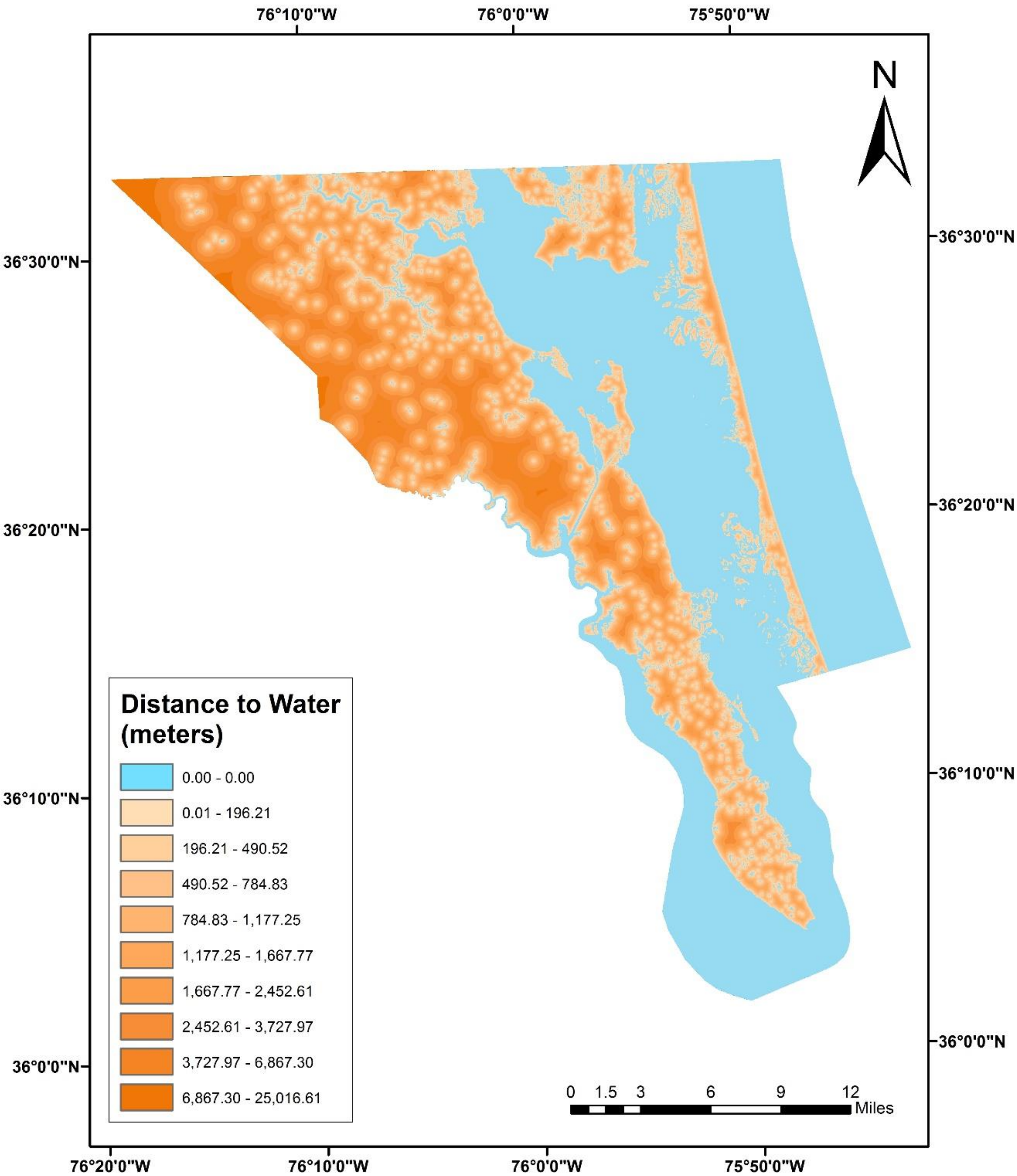



Figure 2-7: Spatial distribution of flood risk factor “distance to water”. (Source: https://www.mrlc.gov/)

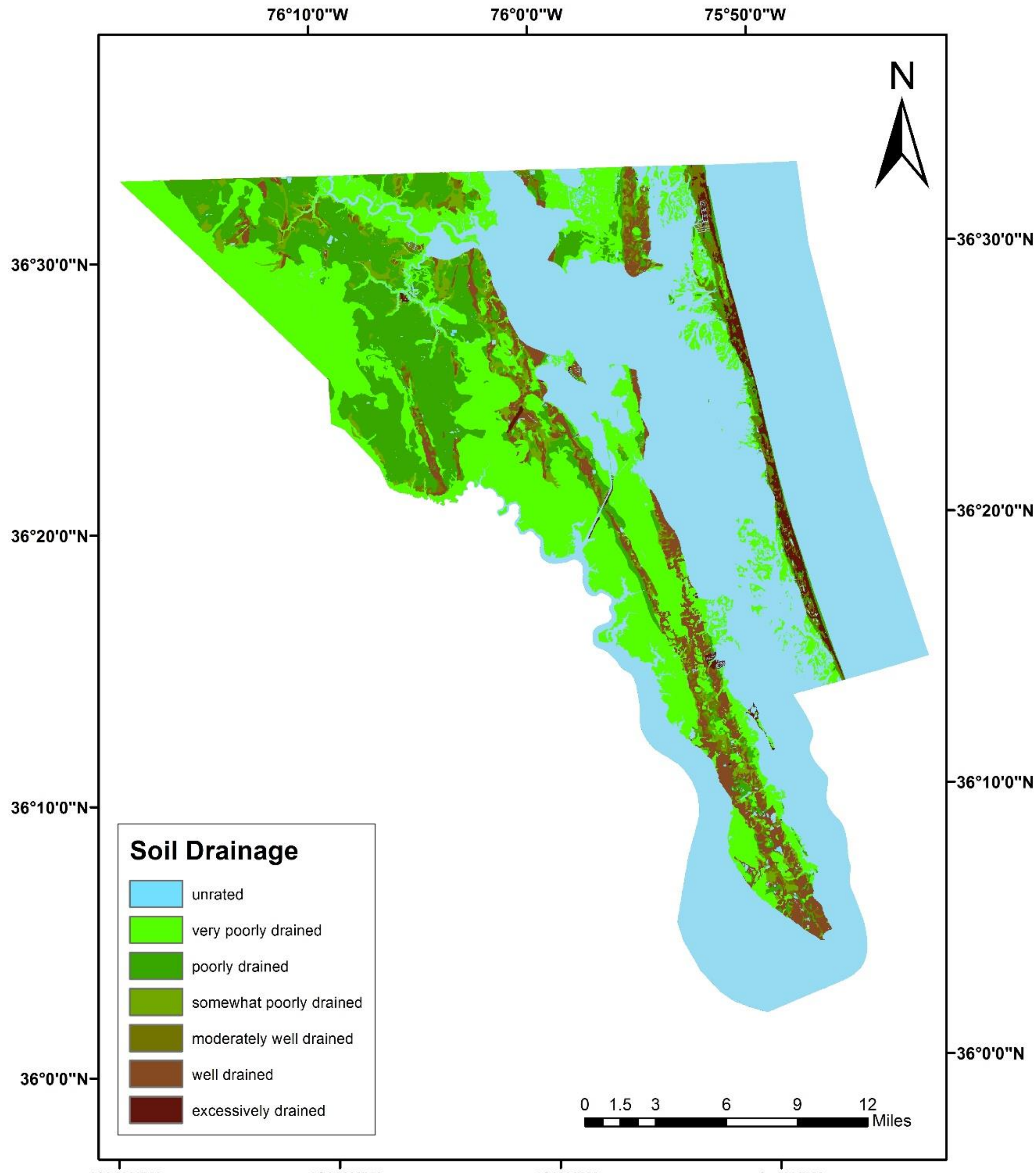



Figure 2-8: Spatial distribution of flood risk factor “soil drainage”. (Source: https://sdmdataaccess.nrcs.usda.gov)

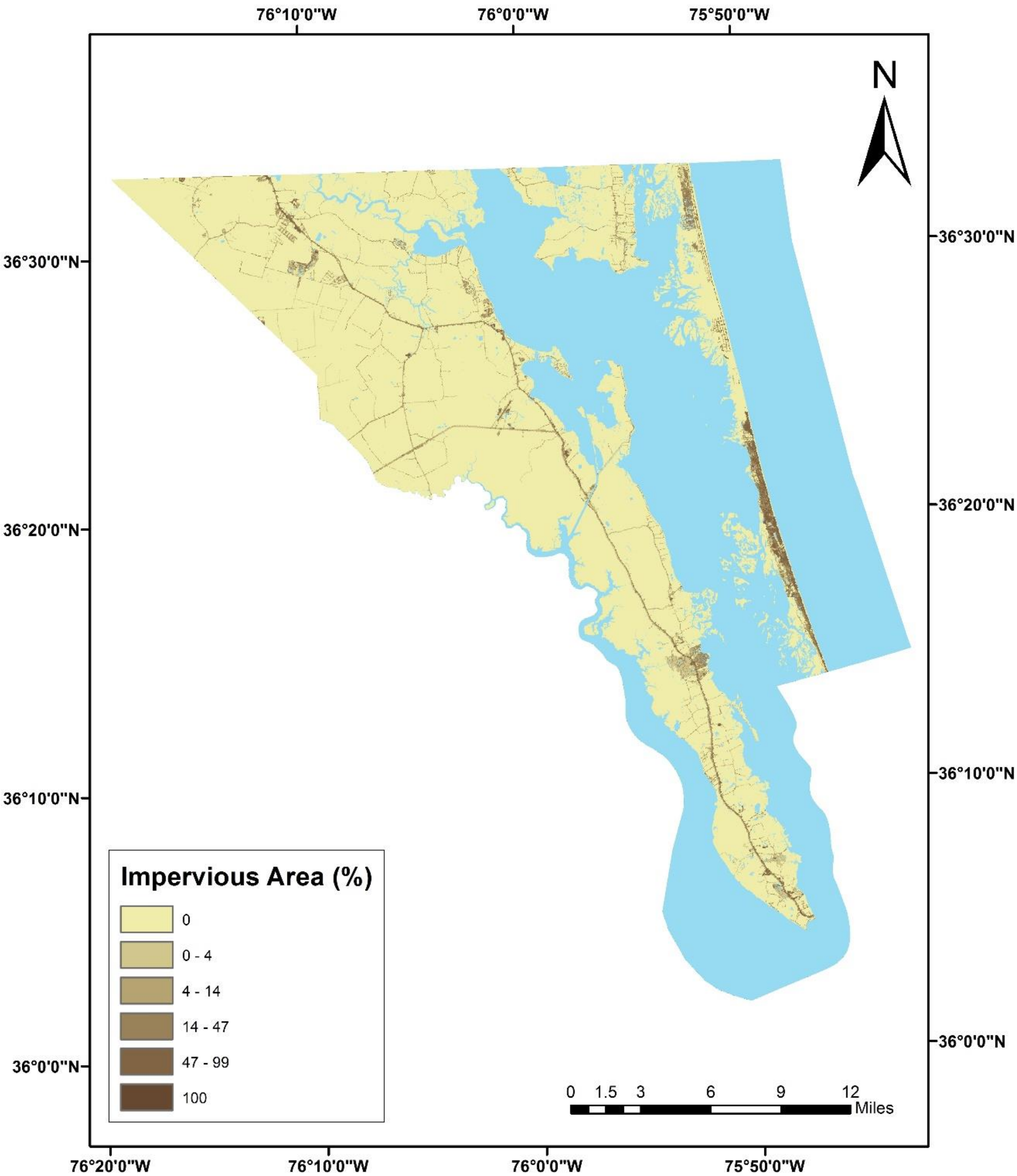



Figure 2-9: Spatial distribution of flood risk factor “impervious area”. (Source: https://www.mrlc.gov)

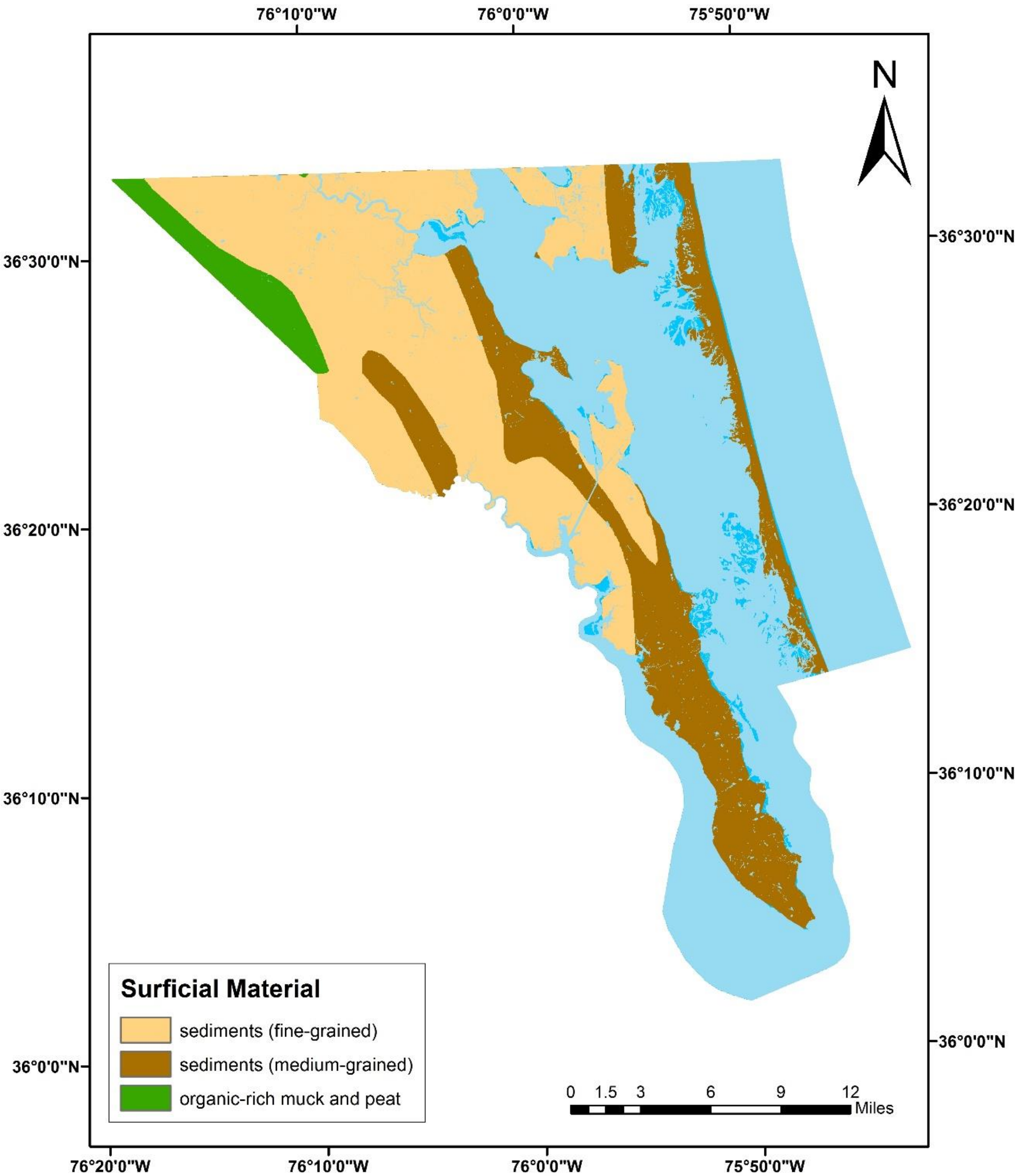



Figure 2-10: Spatial distribution of flood risk factor "surficial materials". (Source: https://pubs.usgs.gov/ds/425/)

## 4. FLOOD INUNDATION

The overall objective is to develop relationships between flooding and all dependent variables (flood risk factors). Therefore, a method is required to compare the values of each factor at a point with whether flooding would be expected or not expected to occur at that point for a specific flood event or flood recurrence frequency. This was initially going to be accomplished using satellite images during a severe flood event that occurred within the last 15 years with sufficient spatial resolution to show maximum spatial inundation. Due to limited access to high-quality satellite data during such an event, it was decided to focus on coastal flood susceptibility and compare flood risk factors to flood inundation as defined by the 100-yr FEMA Special Flood Hazard Area (SFHA) for the region (Fig. 2-11). It was assumed that estimated correlations between flood risk factors using the SFHA and flood inundation due to a coastal event are similar regardless of whether a specific observed flood event is used as compared to the SFHA. Alternatively, if flood susceptibility due to pluvial flooding was desired, observations from actual events would be required. Flood inundation data from the SFHA were compiled into a spatial database using the ArcGIS 10.2 software and resized to a 30 m x 30 m grid; the grid of Currituck County was constructed using the Area of Influence (AOI) shown in Fig. 2-1.

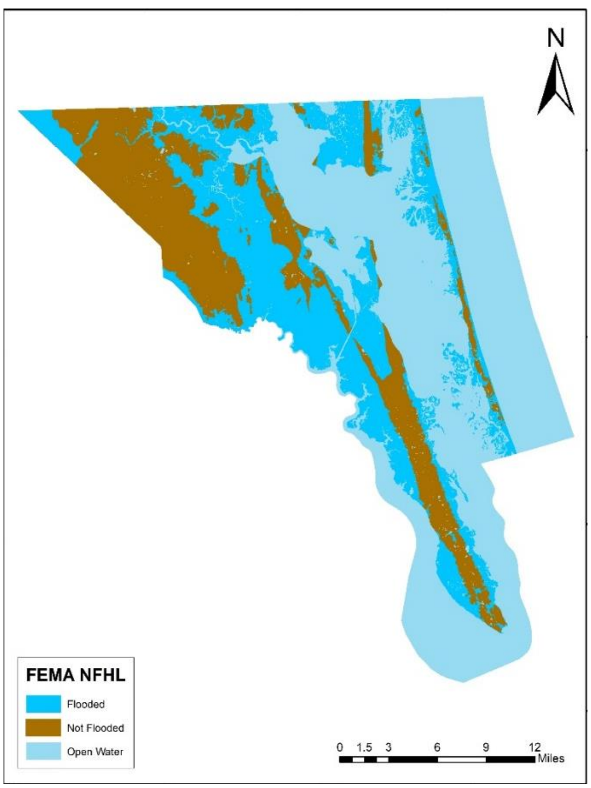



Figure 2-11: 100-year FEMA national flood hazard layer over Currituck County.

# 5. LOGISTIC REGRESSION

Logistic regression, which is a statistical method for analyzing a dataset in which there are one or more independent variables that determine a binary (yes or no) outcome, is then implemented to develop a specific formula that measures the probability of flood inundation throughout the Area of Interest (AOI) during the 100-year flood event. This is accomplished by designating several points throughout the AOI as testing points from which the logistic regression will be derived. Approximately 5 percent of the total number of “30m x 30m” cells that make up Currituck County in this analysis, or 86,122 cells equal to an area of near 30 square miles, were randomly chosen throughout Currituck County with the stipulation that an equal number of those points (43,063) were within and outside of the SFHA (illustrated in Fig. 2-12).

Flood data for all points consisted of either a 0 or a 1 to represent whether a location was not flooded or flooded, respectively; these values represented the dependent variable (L) in the logistic regression:

$$ln\left(\frac{p}{1-p}\right) = L = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n, \qquad (1)$$

where p is the probability of flooding. All flood risk factor data at each location was categorized into classes according to the class ranges designated in Table 2-2 and represented the independent variables ($x_1$ to $x_n$; $n = 9$) in the logistic regression in Eq. 1. In some cases, the ‘land cover’, ‘soil class’, and/or ‘surficial materials’ risk factors were classified as ‘open water’ and/or the ‘distance to water’ was equal to zero even though the location was located outside of any body of water. These points were eliminated from the analysis, which resulted in the total number of points being utilized in the study to be 85,681. The independent and dependent variables were then analyzed using the logistic regression function in R Statistical Software (R) to determine the regression intercept ($a_0$) and the coefficients ($a_1$ to $a_n$; $n = 9$) for each flood risk factor in Eq. 1.

After the coefficients of the logistic regressions are determined for each class of each flood risk factor, the following equation, which is derived from Eq. 1, is used to calculate the probability of flooding at each map grid cell in the final flood susceptibility map. It should be noted that all flood risk factors are used but that for each flood risk factor only one coefficient is used that corresponds to the appropriate factor class (see Table 2-2) at each map grid cell:

$$p = {e^L}/{(1 + e^L)} \cdot \qquad (2)$$

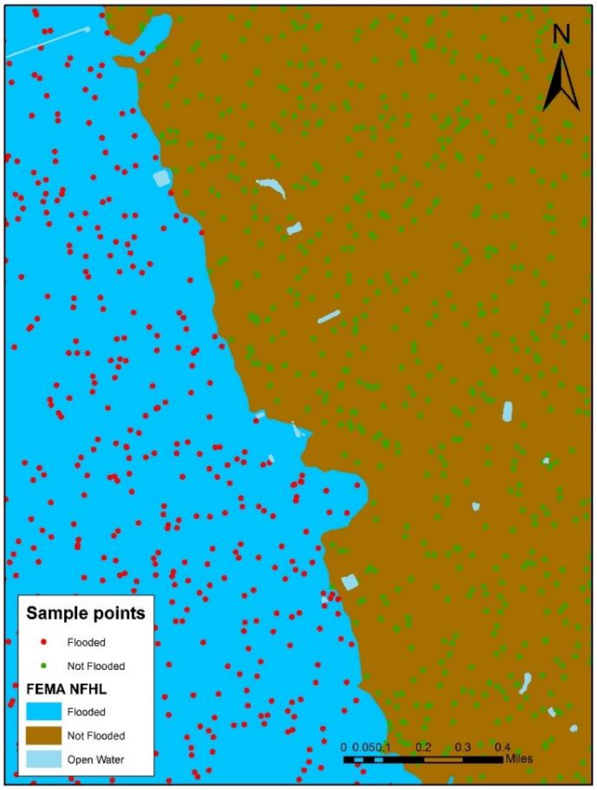



Figure 2-12: Map of a zoomed-in portion of Currituck County showing the distribution of sampling points used to train the logistic model in relation to the boundary of the SFHA. Green points represent locations where flooding did not occur, while red points represent locations where flooding did occur.

## 6. CRITICAL INFRASTRUCTURE

The final step of the methodology related to the development of the flood susceptibility map involves identifying vulnerable critical infrastructure. The geographic information (GIS) data sets include:

- Dams
- Airports
- Hospitals and other health-related facilities
- Fire and police stations
- County facilities
- Private and public K – 12 schools

- Major routes
- Bridges
- Railroads

Data sets and sources related to critical infrastructure throughout Currituck County and that were used in the current study are given in Table A-2 in Appendix A. All critical infrastructure datasets were clipped to the regional boundaries of Currituck County and overlaid onto the final flood susceptibility map.

## 7. RESULTS

The coefficients resulting from the logistic regression are given in Table 2-2 for each class of each flood risk factor. The greater the magnitude of the coefficient, the stronger the impact of that risk factor class on flooding in the AOI. The average regression coefficient values for all flood risk factors are illustrated in Figure 3-1. There are three flood risk factors that stand out as having a dominant correlation with flood susceptibility throughout Currituck County: 'elevation' (ELEV), 'land slope' (SLOPE), and 'soil drainage class' (SOIL). The fact that elevation appears to have the highest influence is not surprising due to the impacts of storm surge within the region. The results of the logistic regression for the initial set of data points were then applied to all map grid cells in Currituck County to produce a flood susceptibility map for the entire region applicable to the 100-year flood event (Fig. 3-2). Flood susceptibility values are plotted as the percent chance that each 30 m x 30 m grid cell will be flooded and then classified into five categories according to the color scale shown in the figure: very low risk (0 – 20%), low risk (20 – 40%), medium risk (40 – 60%), high risk (60 – 80%), and very high risk (80 – 100%). The largest areas of 'very high' and 'high' susceptibility are located on Knott's Island, the Outer Banks, and the mainland along Currituck Sound, as well as along the Northwest and North Rivers and their tributaries. There is also an area of high susceptibility in the northwest corner of the region due to a number of flood risk factors not related to proximity to a water body, such as land cover, soil drainage, and high tree canopy density. The fact that this area consists of high-density woody wetlands (Figs. 2-5 and 2-6) and is characterized by very poorly drained soil conditions (Fig. 2-8) contributes to its high flood susceptibility. It is important to note that at locations where data for one or more flood risk factors was unavailable, we were unable to calculate the flood susceptibility, which was assigned as "undetermined".

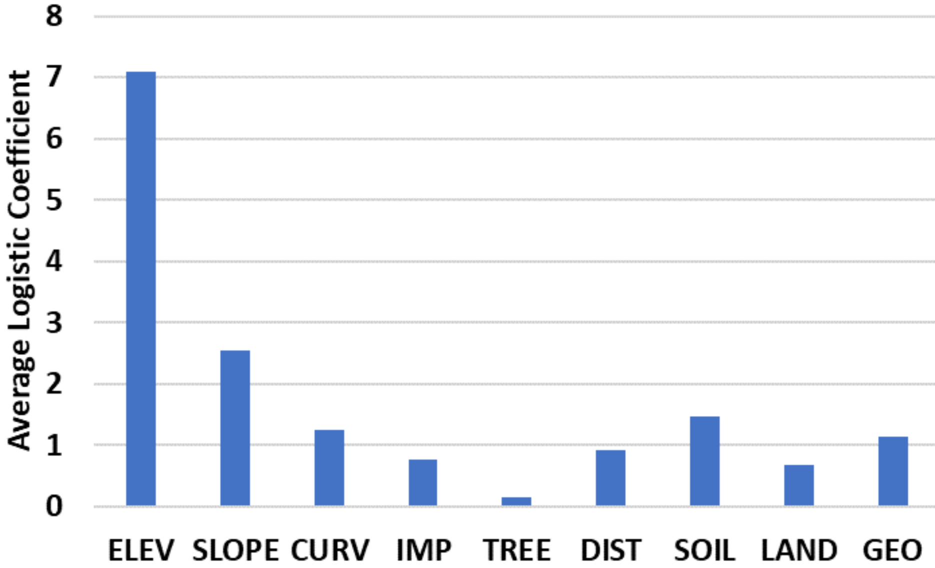



Figure 3-1: Average absolute value of the logistic regression coefficients computed for each flood risk factor.

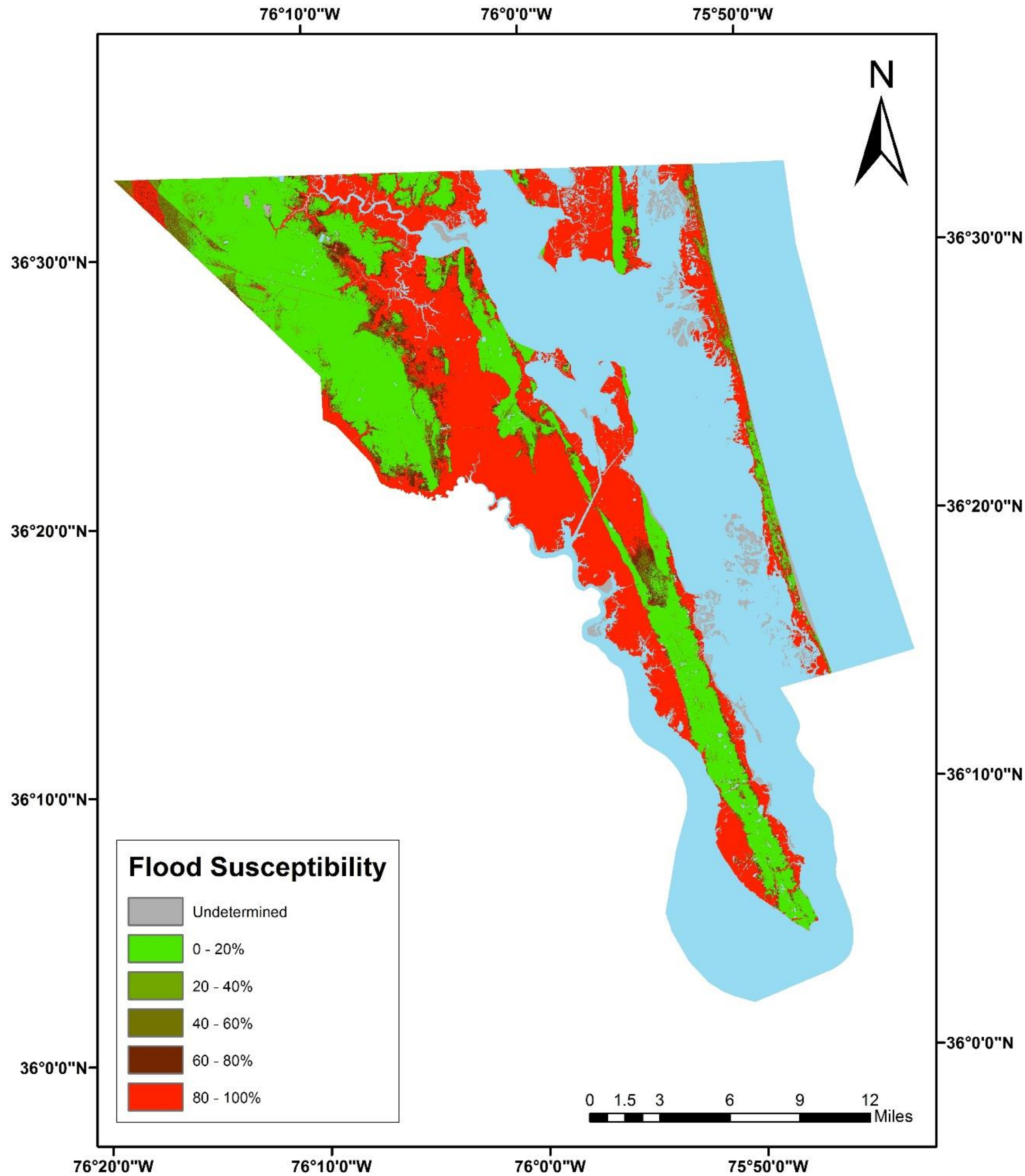



Figure 3-2: Flood susceptibility map of Currituck County using the 100-year FEMA SFHA. Levels represent probabilities of flooding: Very Low: 0 – 20%; Low: 20 – 40%; Medium: 40 – 60%; High: 60 – 80%; Very High: 80 – 100%.

When comparing the susceptibility mapping to the FEMA SFHA, it is important to understand key distinctions between the two. The SFHA is limited to the sub-watersheds of greater than one square mile that FEMA chose to study with limited financial and computational resources. Other limiting factors are the age of the underlying studies illustrated by the FEMA maps (often more than two decades old) and their focus on only areas where development existed or was imminently anticipated. FEMA's flood mapping is developed using physical models to perform hydrologic and hydraulic analysis of a statistical rainfall event with a one percent chance of being equaled or exceeded in any given year (referred to as the 100-year flood). In general terms, hydrologic analysis is the study of transforming rainfall amount into quantity of runoff. Hydraulic analysis takes that quantity of water and uses a physical model to route it through existing terrain, while considering such factors as topography and vegetative density. This modeling is referred to as "detailed analysis." Some areas are studied by "approximate methods." In general, areas studied by approximate methods use a simplified hydrologic analysis methodology and route runoff quantity through best available topography alone.

The susceptibility maps from this study provide a less expensive method of covering all land area within the region. By using the statistical modeling methodology described in this report it was possible to identify the contribution of flood factors within the physically modeled FEMA SFHA and apply them to the entire study region to identify areas thought to be vulnerable to flooding. One important disclaimer about the flood susceptibility map is that it was created for present-day conditions and is only to be used for planning purposes. It is not intended to replace the FEMA mapping for regulatory or flood insurance decisions.

The scale of the flood susceptibility map and data are most appropriately used at the regional scale. However, use of the data at the municipal scale should allow local officials to examine areas of concern for planning purposes. As more accurate input datasets (e.g. higher resolution LiDAR data and imagery) become available, they can be easily incorporated into an updated flood susceptibility analysis. Higher resolution input datasets also allow smaller areas to be analyzed in more detail if desired (e.g. the City of Coinjock and other communities along Highway 158 in the center of the map, which are dominated by areas of 'very high' flood susceptibility in Fig. 3-2).

Data sets for various types of critical infrastructure (listed in Table A-2) were obtained and overlaid onto the final flood susceptibility map for Currituck County (Fig. 3-3). Several critical infrastructure, and a large portion of the major routes and railroad in the central portion of the county, are included within the 'high' and 'very high' risk areas of 100-year flood susceptibility.

It is also observed that almost all areas identified as having “high” to “very high” flood susceptibility to the 100-year flood are included in the FEMA SFHA. There are a few exceptions, particularly along the northern Outer Banks as can be observed using the zoomed-in maps shown in Fig. 3-4 (locations within the county are indicated by the rectangles in Fig. 3-3). Figures 3-4a – c reveal several areas where flood susceptibility ranges from ‘medium’ to ‘very high’ that are located outside of the SFHA moving from north (Fig. 3-4a) to south (Fig. 3-4c). In particular, almost half of the area located outside of the SFHA in Fig. 3-4a is classified as being susceptible to 100-year flood events. In addition to road, there are critical infrastructure located in areas of high susceptibility (Figs. 3-4b and c) for which additional flood mitigation efforts may be warranted.

It should be noted that as the flood susceptibility map provides a guide for future planning and flood preparedness related to critical infrastructure and other facilities, it is not meant to provide additional information to be used for flood insurance or regulatory purposes; this is the purpose of the FEMA map or hatched area in Fig. 3-3.

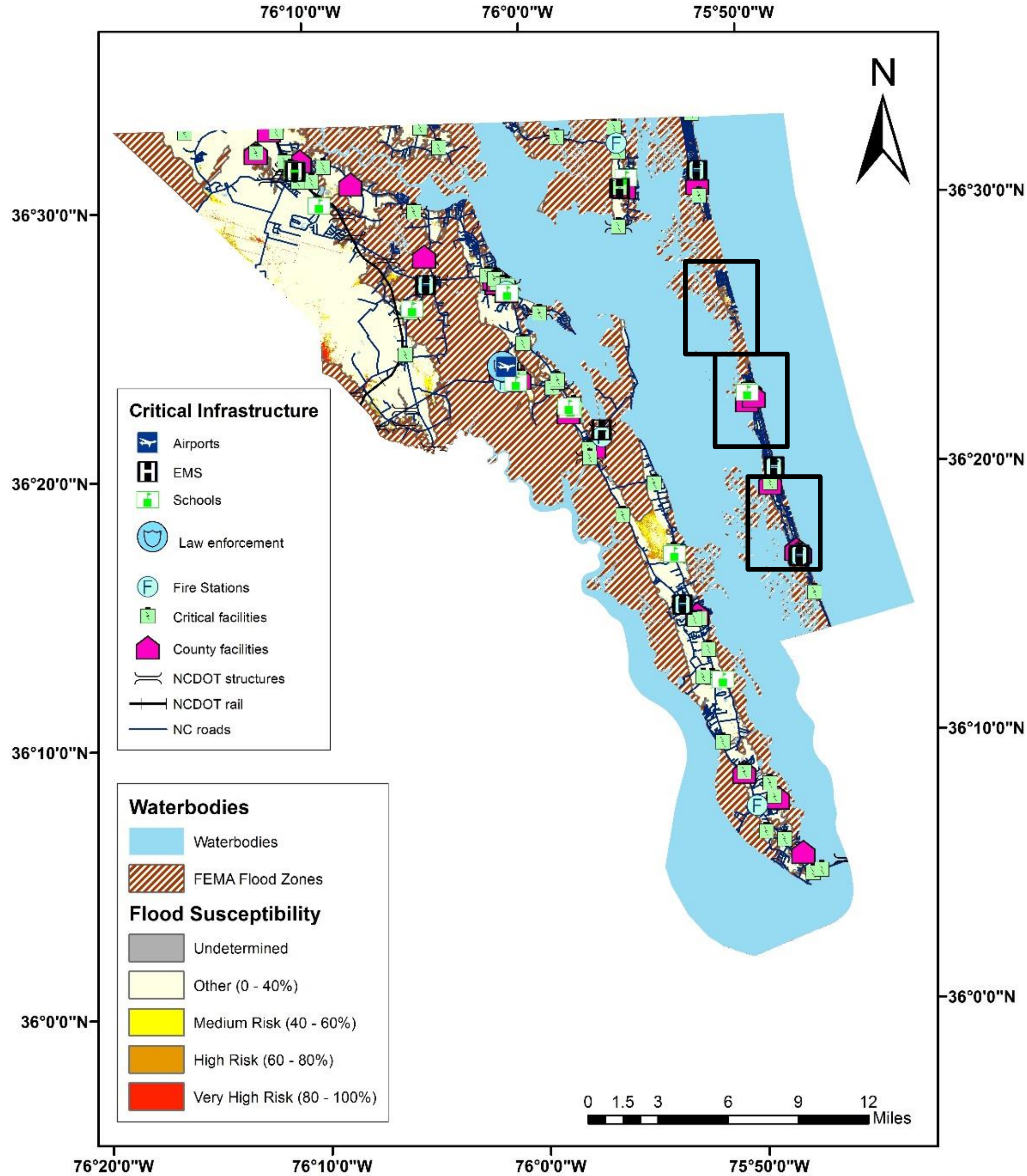
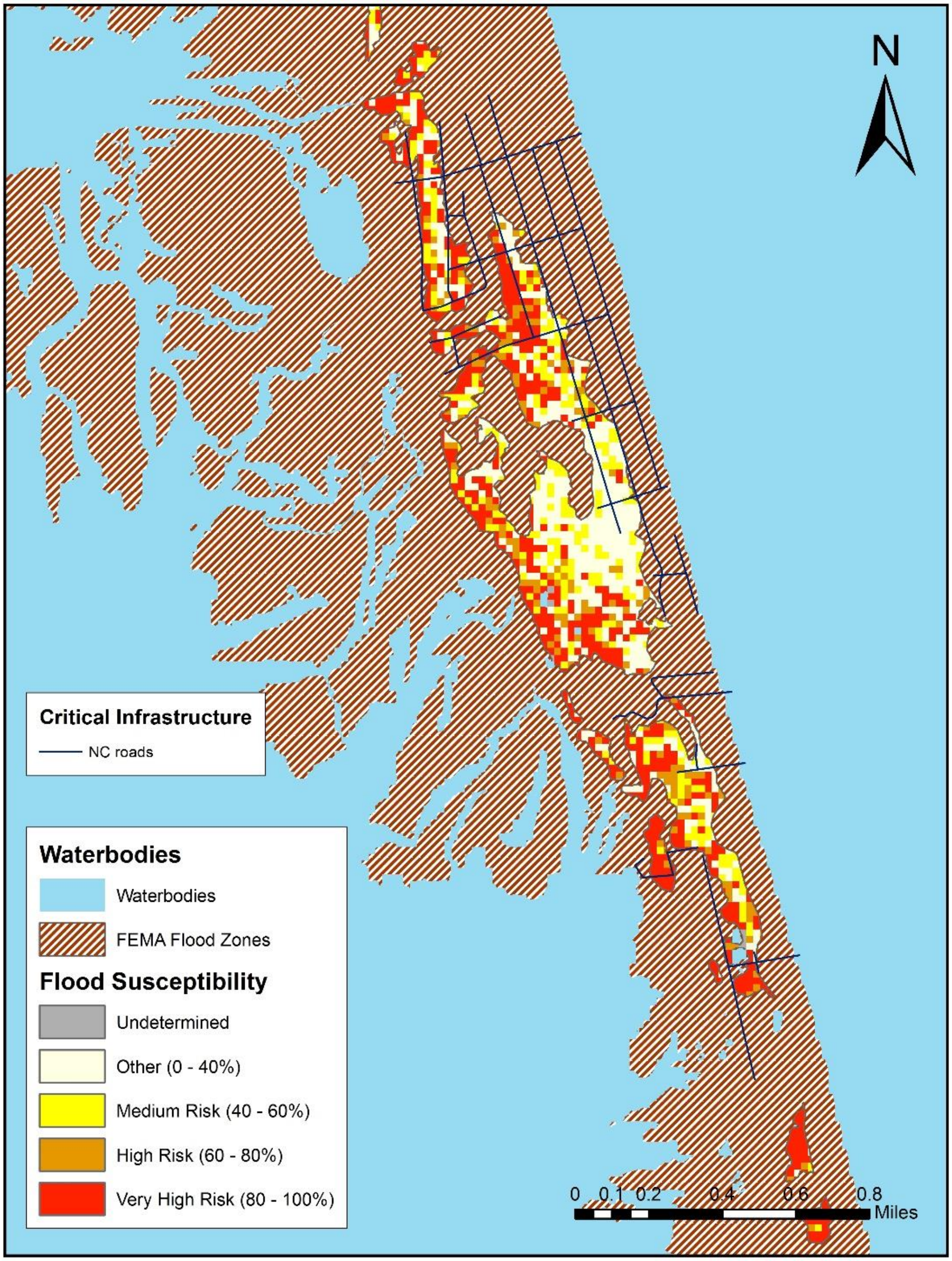
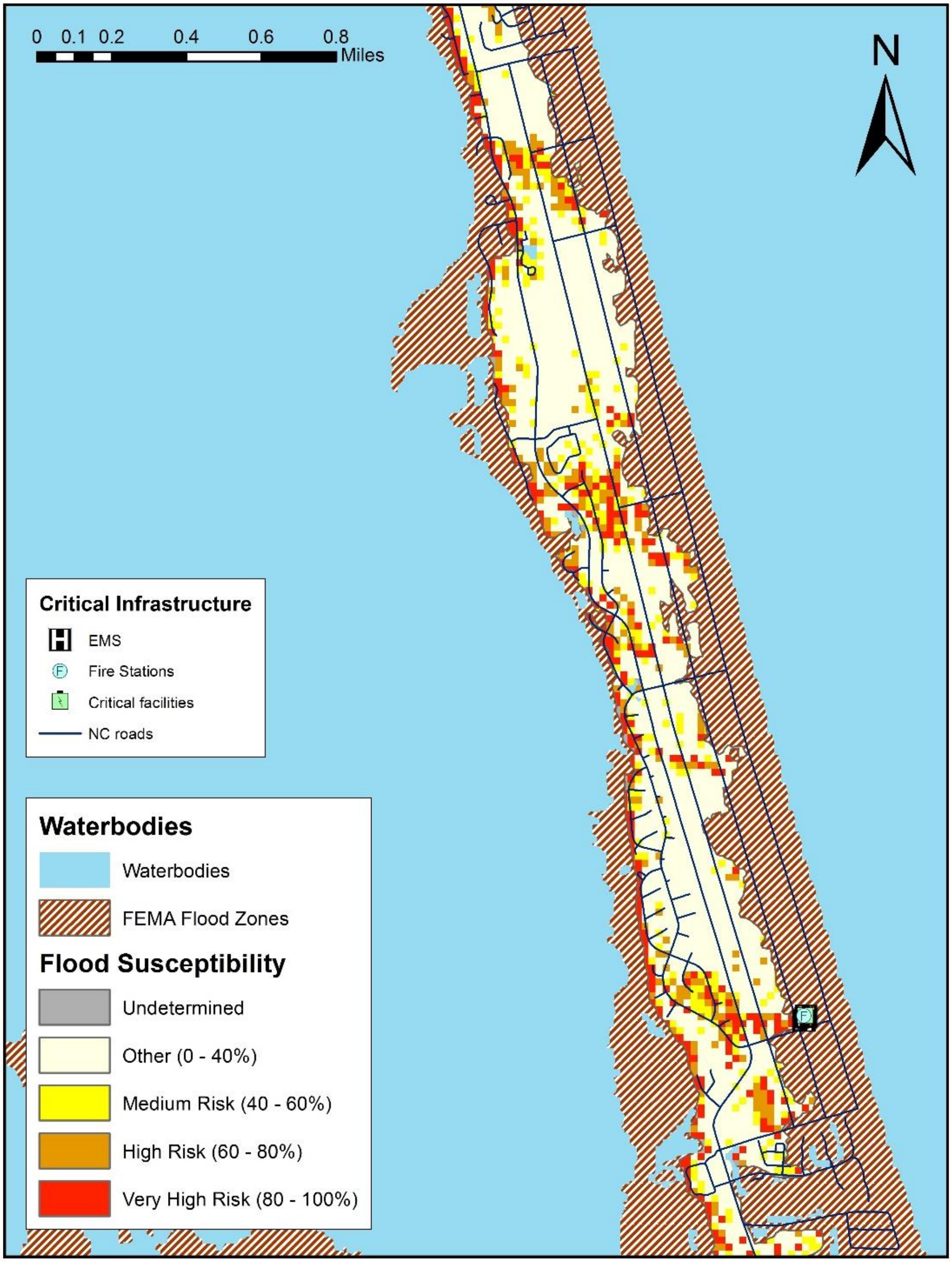


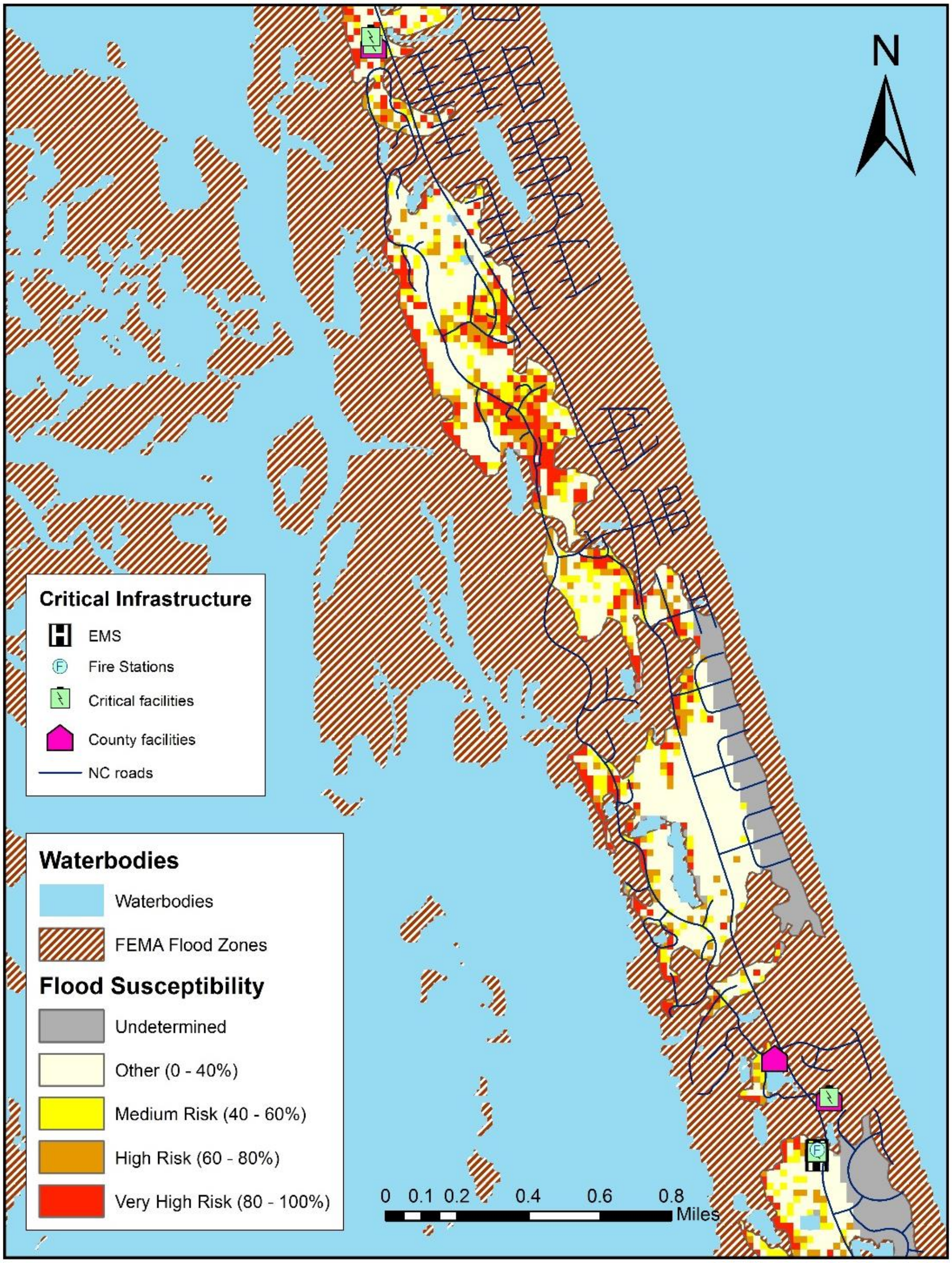

Figure 3-3: Locations of various vulnerable critical infrastructure relative to areas of 'Medium' (dark green), 'High' (dark red), and 'Very High' (red) flood susceptibility. The 100-year FEMA SFHA (hatched) is also included for reference and comparison. Boxes represented sub-regions analyzed in more detail in Fig. 3-4.


N
Critical Infrastructure
NC roads
Waterbodies
Waterbodies
FEMA Flood Zones
Flood Susceptibility
Undetermined
Other (0 - 40%)
Medium Risk (40 - 60%)
High Risk (60 - 80%)
Very High Risk (80 - 100%)
0 0.1 0.2 0.4 0.6 0.8
Miles

(a)


0 0.1 0.2 0.4 0.6 0.8
Miles
N
Critical Infrastructure
EMS
Fire Stations
Critical facilities
NC roads
Waterbodies
Waterbodies
FEMA Flood Zones
Flood Susceptibility
Undetermined
Other (0 - 40%)
Medium Risk (40 - 60%)
High Risk (60 - 80%)
Very High Risk (80 - 100%)

(b)




(c)

Figure 3-4: Comparison of locations having 'medium' (yellow), 'high' (orange), and 'very high' (red) flood susceptibilities that lie outside of the FEMA SFHA (red-hatched area) for three sub-regions (a, b, and c) along the northern Outer Banks; critical infrastructure is overlaid on the map. Specific locations of each sub-region are shown by the boxes in Fig. 3-3.

## 8. H & H STUDY PLANNING FRAMEWORK

The following analytic framework was developed to assist the task of prioritization and planning for detailed hydrological and hydraulic (H & H) studies. Figure 3-5 outlines the process for identifying drainage basins and performing detailed H & H analysis aimed at developing hazard mitigation strategies and solutions.

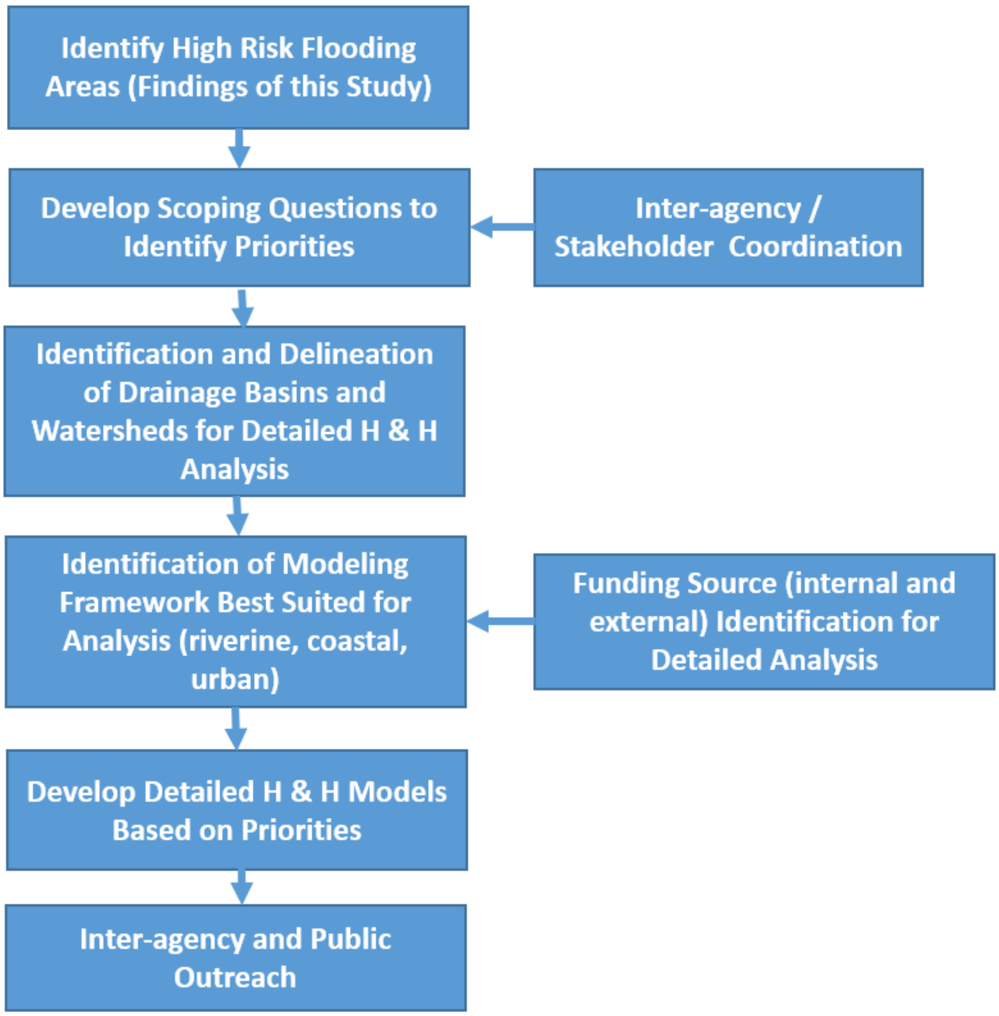



Figure 3-5: Detailed H & H Analysis Process Flow

The following is a set of scoping questions incorporating the priorities, concerns and needs of various agencies and stakeholders, to be used as evaluation criteria for detailed H & H study area selection:

1. What are the main areas of susceptibility identified based on watershed conditioning factors (results of this study)?
2. What public facilities are in areas of substantial vulnerability and are currently unprotected / under protected?
3. What critical infrastructure facilities (hospitals, emergency response facilities including fire stations, shelters, etc.) are in areas of substantial vulnerability, and are currently unprotected / under protected.
4. Roadway infrastructure criteria:
    a. How many, and what are the locations of the State and County owned roadways that connect rural areas of the County to interior parts of the County, which are highly vulnerable?
    b. What are the existing drainage issues in these roadway networks (undersized culverts, un/under-maintained roadway segments, bridges and culverts, which form the hydraulic pathway of least resistance resulting in flood susceptibility?
5. What are the locations of County Waste Water Treatment Plants (WWTPs), water distribution facilities and systems, and landfill (sanitary and hazardous waste) sites that are in the areas of susceptibility?
6. Are there known issues of sewer and stormwater mixing resulting in hazardous conditions for the environment? If so, what are the sources of and approximate (if known) extent of this type of impact stormwater (only) inundation areas?
7. What are the social assets (historic structures, religious buildings, other health care facilities, etc.) that are identified within the areas of rainfall susceptibility?
8. What are the areas of combined coastal, fluvial (riverine), and pluvial (rainfall) influence?
9. What are the high priority assets and resources from an environmental, ecosystem and habitat stand point (including wetlands and shorelines)? Based on inputs received from The Nature Conservancy's Office of Coastal Engagement, the following are some items to consider:
    a. Areas in the Northwest part of the County and north river watershed.
    b. Areas identified as high priority under NC Heritage significant natural areas.
    c. Areas identified as "resilient", i.e. ranked as equal to greater than average in The Nature Conservancy's "Resilient Coastal Sites"
    d. Areas of migration space / Sea Level Rise (SLR) buffer.

10. What are the current, near-term and long term development goals and / or restrictions by the County, including full service areas?
11. What are the possible ways to obtain and /or collect missing data that resulted in "undetermined" flood susceptibility in this study?
12. What are the key climate variability aspects (sea level rise, increased precipitation, extreme temperatures) to be considered while identifying and prioritizing basins for detailed watershed studies?
13. How does the County intend to best use the findings of this study to articulate, educate and invite participation from the residents and agencies involved to plan for and implement long term resiliency measures?

## 9. SUMMARY

A flood is one of the most severe and potentially devastating natural disasters. Awareness of areas that are currently prone and will become more prone to flooding in the future is essential to consider in short-term, as well as long-term, planning. Such awareness comes from an understanding of a combination of not only regional climatic factors, but also of non-climate factors that relate to regional and site characteristics.

The current study estimated flood susceptibility within Currituck County, North Carolina, due to non-climatic factors. The method used to look at flood susceptibility involved performing a logistic regression to determine the relationship between several flood risk factors and flooding at the 100-year recurrence level within the county. It was found that 'elevation', 'land slope, and 'soil drainage class' have the most influence on flood susceptibility in the region. The coefficients that resulted from the logistic regression were then used to create an overall flood susceptibility map for Currituck County onto which various types of critical infrastructure were overlaid. Large areas with "very high" and "high" susceptibility where such infrastructure are located were identified within the central portion of the county and well as the northern Outer Banks. Although the regional data is not at a scale large enough for local determinations, these hotspot areas warrant further consideration for future localized flood susceptibility mapping if future suitable data sets become available and further consideration at the municipal resiliency planning level.

Minimal differences were observed between the 100-year susceptibility map and the 100-year FEMA SFHA throughout most of the county because land characteristics that correlated with flooding did not extend beyond the limits of the SFHA. With that said, there were a few areas of 'medium' to 'very high' susceptibility found along the Outer Banks where land characteristics similar to those found within the SFHA extended outside of the limits of the

SFHA as well and that warrant additional attention. One important disclaimer about the flood susceptibility map is that it was created for present-day conditions and is only to be used for planning purposes. There are several prominent factors that could affect the *future* flood susceptibility map: changes in impervious area (through urbanization), a higher sea level (for coastal areas) and heavier precipitation. A *future* flood susceptibility map can be created by studying how these factors are expected to change. However, it is expected that the present-day flood susceptibility map provides an excellent relative foundation from which to consider future changes. In other words, it is logical to assume that higher-risk present-day regions will remain as higher-risk regions in the future.

These conclusions demonstrate the importance of determining which present-day recurrence intervals (e.g. 100-year) are important for land use and recovery planning, hazard mitigation, zoning, design standards and/or flood warning plans. Socioeconomic models can then be built to show how a more frequent occurrence of such events will impact response and/or recovery costs.

## 10. FUTURE WORK

Projects and studies that utilize novel methods in accomplishing their final objectives typically identify several additional new directions in which to extend the work as well as additional questions that come up because of the analysis and conclusions. The current project is no exception with the following list providing potential avenues for future work:

- Utilize local expert and resident experiences related to flooding in the region to ground-truth the 100-year flood susceptibility map that was developed in the current study.
- Maintain awareness of data collection for future events. Given the increase in forecast skill of severe floods, it may be possible for Currituck County to work with its neighbors/partners to make sure that any future flood inundation events are well sampled by specialized satellite and/or synthetic aperture radar missions. These would provide the horizontal resolution to significantly enhance the current model past the 30-m grid size.
- Create additional flood susceptibility maps for more frequent flood exceedance frequencies using the method used for the 100-year flood events. This is limited by the availability of satellite data during maximum inundation caused by the flood, but images for very frequent events (e.g. 5-year) should be available and would provide inundation information for floods that are considered a frequent annoyance rather than a potentially rare disaster.
- Re-run the analysis for future flood events. If and when a flood event occurs in the future within Currituck County and resources and satellite imagery permitting, recreate

a flood susceptibility map for the exceedance frequency associated with the event. The final goal would be to analyze a sufficient number of events of varying frequencies to enable interpolation of the risk factor regression coefficients for any flood event exceedance frequency.

- Identify, obtain and collect (if necessary) missing data that resulted in the assignment of "undetermined" flood susceptibility.
- Encourage the development of improved datasets related to flood risk factors that were identified as having substantial impacts on flooding in each sub-region; this would include the flood-risk factors 'elevation', 'distance to water', and 'land cover'. Improved resolutions (e.g. 30 meters to 1 meter) of each input dataset would contribute substantially to improved flood susceptibility maps at any desired exceedance frequency.
- As resources permit, flood susceptibility map(s) should be revised, which includes rerunning the analysis described in this report, as improved datasets of flood risk factors become available.
- Using the framework developed as part of this study, identify areas for detailed H & H analysis based on priority ranking, inter-agency and multi-stakeholder collaboration.

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# APPENDIX A: Input Data Metadata

Table A-1: Flood risk factors and flood event data with data source and resolution/scale.

| Flood Risk Factors | Source (year) | Resolution/Scale | URL for Data Access |
|---|---|---|---|
| **Land Cover (LAND)** | USGS (2011) | 30 meters | https://www.mrlc.gov/ |
| **Elevation (ELEV); Slope (SLOPE); Curvature (CURV)** | USGS (2014; 2011) | 30 meters | https://earthexplorer.usgs.gov/ |
| **Distance from Water (DIST)** | USGS (2014) | 1:24,000 | https://www.mrlc.gov/ |
| **Soil Drainage (SOIL)** | USDA-NRCS (current) | varies | https://sdmdataaccess.nrcs.usda.gov/ |
| **Vegetation density (VEG)** | USGS (2011) | 30 meters | https://www.mrlc.gov/ |
| **Impervious Surface (IMP)** | USGS (2011) | 30 meters | https://www.mrlc.gov/ |
| **Surface Geology (GEO)** | USGS (2009) | 1:24,000 | https://pubs.usgs.gov/ds/425/ |
| **FEMA 100-year Hazard Area** | DHS/FEMA (2016) | 1:12,000 | https://catalog.data.gov/dataset/national-flood-hazard-layer-nfhl |

Table A-2: Critical infrastructure data sets used in the current study with data source and link.

| Infrastructure | Source (Year) | URL for Data Access |
|---|---|---|
| **Airports** | Currituck County (2018) | http://co.currituck.nc.us/geographic-information-services/ |
| **Bridges** | NCDOT (2018) | https://connect.ncdot.gov/resources/gis/pages/gis-data-layers.aspx |
| **County Facilities** | Currituck County (2018) | http://co.currituck.nc.us/geographic-information-services/ |
| **Fire Stations** | Currituck County (2018) | http://co.currituck.nc.us/geographic-information-services/ |
| **Health** | NC OneMap (2018) | http://data.nconemap.com/geoportal/catalog/main/home.page |
| **Police Stations** | NC OneMap (2017) | http://data.nconemap.com/geoportal/catalog/main/home.page |
| **Railroads** | NCDOT (2018) | https://connect.ncdot.gov/resources/gis/pages/gis-data-layers.aspx |
| **Major Routes** | NCDOT (2018) | https://connect.ncdot.gov/resources/gis/pages/gis-data-layers.aspx |
| **Schools** | Currituck County (2018) | http://co.currituck.nc.us/geographic-information-services/ |

www.dewberry.com